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HMM as an Inference Technique for Context Awareness

Ahmad Faridi[a]*, M.M. Hafizur Rahman[b]

[a,b] *Department of Computer Science, IIUM, Kuala Lumpur and 50728, Malaysia*

Abstracts

Context awareness is an important element in the pervasive and ubiquitous computing. It involves the ability of the computing system to be aware of the context in which a particular target user is experiencing. This involves the location in which the target is, the activity that the target is doing, the identity of that target and the time in which the activity occur. Once these two elements are known we propose the use of HMM to predict and infer the context of the user.

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*Keywords:*context awareness; hmm;

1. Introduction

The ability of a computing system to be immersed into an environment, aware of its surrounding environment, interact with it, and provide a response to environmental changes is generally describes what is known as ubiquitous computing (Ubicomp). The concept of ubiquitous computing appeared as a result of the migration from the traditional computing paradigm that involves physical systems that are bound spatially and physically to a paradigm that is more mobile and not bound by the static physical location of the computing system. At the early beginnings of computerized systems, concentration was basically on evolving the physical attributes of a computing system. i.e. shifting these systems in terms of size, interface, portability etc. Despite the immense changes at these areas throughout the years, limited significant progress was seen in the automated interaction of the computing system with its continuously changing environment. However lately different type of sensors started to be used as means to detect different changes in the phone itself and the environment surrounding it[1].These changes are then used to infer

* Corresponding author. Tel.:
E-mail address:

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different responses and services the phone provides. Primarily, the main goal of any inference mechanism is to be help in creating what is known as context sensitive system. The word "context" here refers to as the collective knowledge that is gathered through any of the following elements known as the 6 questions of context: ***When, Where, Who**, **What, How***and ***Why*** [1]. However, some authors simplify the notion of context to only identity (who), location (where), time (when), activity (what)[2]. The rest of the paper will cover a review on HMM, and then its use in context awareness is presented with details on the experiment conducted as well as the results.

1.1. Review

The Hidden Markov Model or HMM is a statistical tool that is used to analyse and predict current states in problems that involve a series of successive instances of data or sequence based on information of previous states. Observations that happen along the time series, DNA sequencing and words are such examples with successive instances. HMM has been applied in a variety of applications ranging from robotics, computer science, speech and natural language processing and finance.

Unlike many other methods of inference, that takes each instance as independent of other instances, Markov Models, and to be precise, Hidden Markov Model, treats instances in samples as dependent on the previous instance in the time series. In a Markov model, an instance a_t at time t (with the exception of the initial instance/state) cannot exist without the previous instance x_{t-1} and x_{t-1} on the other hand depends on $x_{t-2}$and so on.

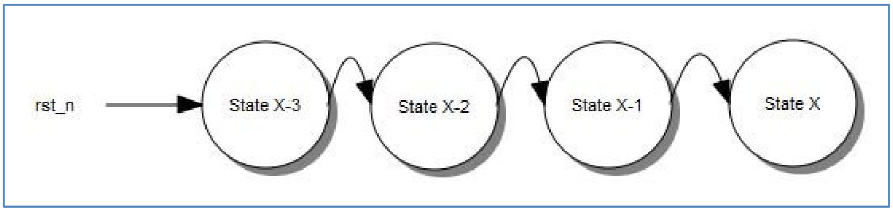

Fig 1: Markov Model

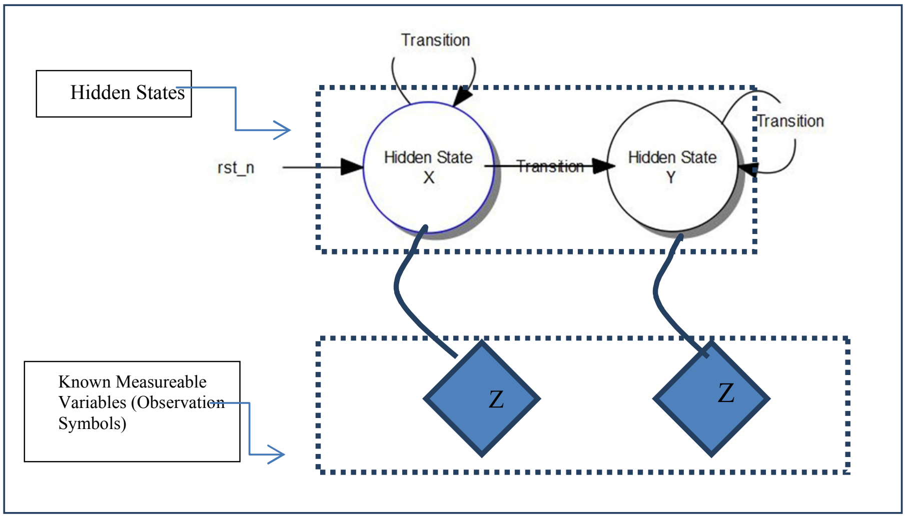

Fig 2: Structure of a typical Hidden Markov Model

Fig 2 shows that for each state, it directly depends on its previous state. It shows the transition from one state to another in a normal *Observable* Hidden Markov Model. It is called *Observable* because the states in question in these cases are known. In a Hidden Markov Model, the assumption is that the physical state is unknown and can only be represented by external observations, hence the term “hidden”. These observations are what are known as the observation symbol (See Fig. 2). To give an example, say that there is a Markov Model of two states; *Pass and Fail*. Let’s assume also, that for each pass a student feels happy, while for each fail the student feels sad. Furthermore, let’s assume that the states are hidden and unknown and that the only means of knowing is through the observable emotions of the students[3]
Mathematically, using HMM for the purpose of prediction and analysis is given through these equations:

$$P(X_1|Z_1): \frac{P(Z_1|X_1)P(X_1)}{P(Z_1)} \qquad (1)$$

$$P(x_2) = \sum_{x_1} P(X_1) \cdot P(X_2|X_1) \qquad (2)$$

Equation 1 handles the determining the probabilities of a certain state X given a certain observable measurement Z. while Equation 2 handles the prediction of a future state X_2 given the previous state(s).
In a nutshell, a typical Hidden Markov Model contains four elements [5]:

1. N: the number of states in the model. $S = \{S1, S2, S3, S4 \ldots., SN\}$
2. M: the number of distinct observation symbols in the alphabet. $V = \{v1, v2, v3 \ldots. vM\}$
3. State transition probabilities. $A = [aij]$ where $aij = P(qt + 1 = sj \mid qt = Si)$
4. Observation symbol probabilities. $B = [bj(m)]$ where $bj(m) = P(Ot = vm \mid qt = Sj)$

The probabilities presented here, i.e. state transition probabilities and observation symbol probabilities are generated by an algorithm known as the Welch-Baum algorithm. This algorithm is normally used to find unknown parameters in the Hidden Markov Model. Given an output sequence and a Hidden Markov Model, the Baum-Welch algorithm seeks to improve the given model to one that is could have more likely generated the given output sequence. It does so by using both the Forward Algorithm and the Backward Algorithm and using the output of these two algorithms to generate or improve the probabilities of the initial probability [4].

2. HMM for Context Awareness

In the domain of context awareness, a technology cannot be described as context aware without at least exhibiting the ability to detect activity and position. Once these elements are available, the next step would be to utilize and inference technique to correctly associate these combination of elements to the correct context. In our case we utilized HMM as our inference and probabilistic technique of choice.

Given the scenario of activities done in a stadium. Table 1, presents the activity-to-location relationships and what each relationship yields. Activities are detected by using mobile devices with embedded accelerometers that is strapped or kept by a particular user. This technique was extensively addressed in previous studies. Using such technique, it is quite possible to determine some basic user activities such as standing, sitting, running, jumping and walking.6,7. Positions and locations, however, are easily detected using modern GPS or positioning techniques. In our scenario presented in table 1, If a user’s activity (for example) is detected as “running” and the location of that activity is detected as the “stadium” or a “play ground”, it is possible then to infer that the said user is exercising.

Table 1: Activity-to-location scenarios.

Activity	location	State
Standing/sitting	Stadium	Resting
Running	Stadium	Jogging/Exercise
Jumping	Stadium	Exercise
Walking	Stadium	Exercise/Commute

As the nature of the activities presented above is continuous, it is then possible to use HMM to continuously predict the next possible activity. As already mentioned earlier, HMM systems consists of several elements. Table 2lists down these elements in relation to our implementation.

Table 2: HMM elements in relation to context awareness.

Elements	Description
N: the number of states in the model.	2states (states related to health and fitness in a stadium). In our scenario we present two states resting and exercising.
M: the number of distinct observation symbols in the alphabet.	2 distinct observation symbols.
State transition probabilities.	These probabilities will be generated using the Baum-Welch method
Observation symbol probabilities.	These probabilities will be generated using the Baum-Welch method

To generate the state transition probabilities, initial state probabilities and, observation symbol probabilities. We present the Baum Welch algorithm with a sequence of observation. This sequence is collected as following procedure:

1. Data collection with a certain duration
2. Volunteers go about doing his activities.
3. Data is collected in intervals.
4. With every data collected (location and activity) the context (state) is added as a label to the data.

These data will be stored in sequence and will be presented to the Baum-Welch algorithm to produce the probabilities needed for the Hidden Markov Model. In our experiment a volunteer was asked to do certain activities in the IIUM sports complex for about 60 minutes. The 60 minutes worth of data along with the initial probabilities that was generated by the Baum-wlech method was then used to create the HMM for the said sequence of activities that happened during the 60 minutes.

The resulting HMM model is then used to predicted subsequentstates and their probabilities. (Table 3)

Table 3: Hidden state probabilities based on the HM model that has been generated

State	Next (Hidden State)	Probability
Resting	Exercise	0.05 or 5%
Resting	Resting	0.94 or 94%
Exercise	Resting	0.011 or 1.1%
Exercise	Exercise	0.875 or 87%

3. Conclusion

This paper focuses on the use of HMM to infer and assist in the process of context awareness. It has been shown that by using HMM it is possible to predict a user's next state given the current state and previous states as been shown in Table 3. The prediction of the next state can be used to proactively present more accurate context awareness. Further additions in the model needs to be addressed, however. This is because, the current model puts into account only two (location and activity) out of four elements of context awareness as we have left out elements of time and identity in our study. It is expected by the addition of the other two elements of context awareness, the model will be even more useful and accurate.

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